

# Understanding Politics via Discourse Contextualization

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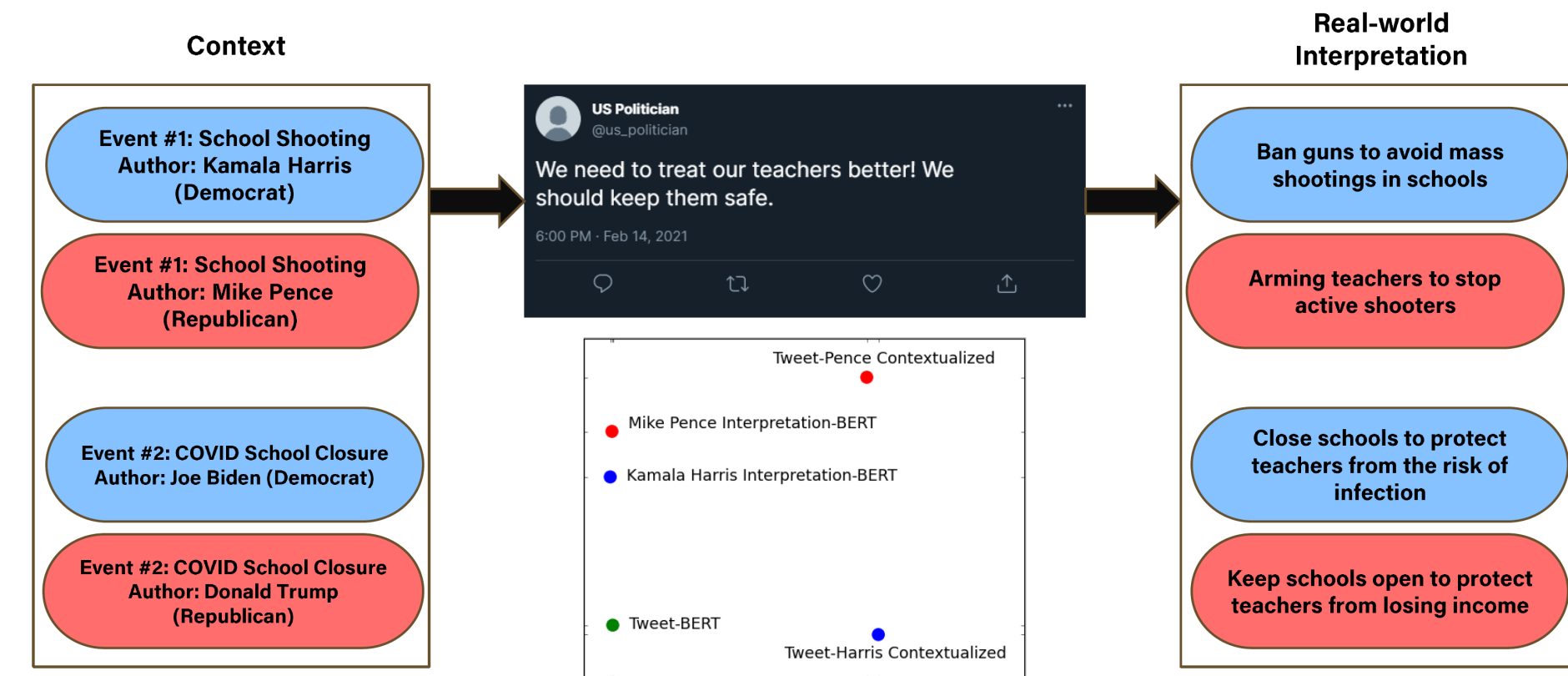
Department of Computer Science

## Abstract

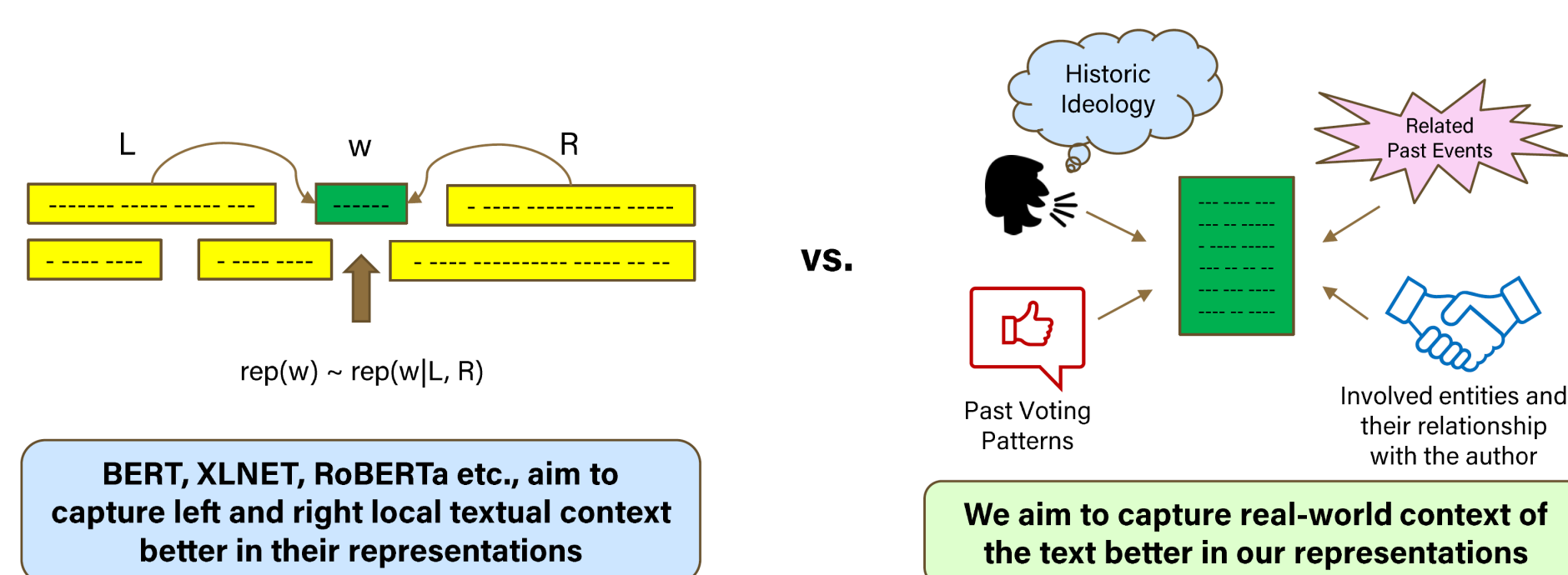
- ▶ Politicians' reactions and arguments in context of various events reflect a fairly consistent set of agendas. In spite of recent advances in Pretrained Language Models (PLMs), those text representations are not designed to capture such subtle nuances.
- ▶ We propose a Compositional Reader model consisting of encoder and composer modules, that captures and leverages such information to generate effective representations for entities, issues, and events.

## Motivation

- ▶ Political text tends to be concise and subtle, especially on social media. Same text could signal starkly different real-world actions depending on the author and the surrounding context. This calls for a representation model that can contextualize based on the real-world context of the text.



## Approach



**Challenge:** How can this massive amount of political content be used to create principled representations of politicians, their stances on issues and legislative preferences?

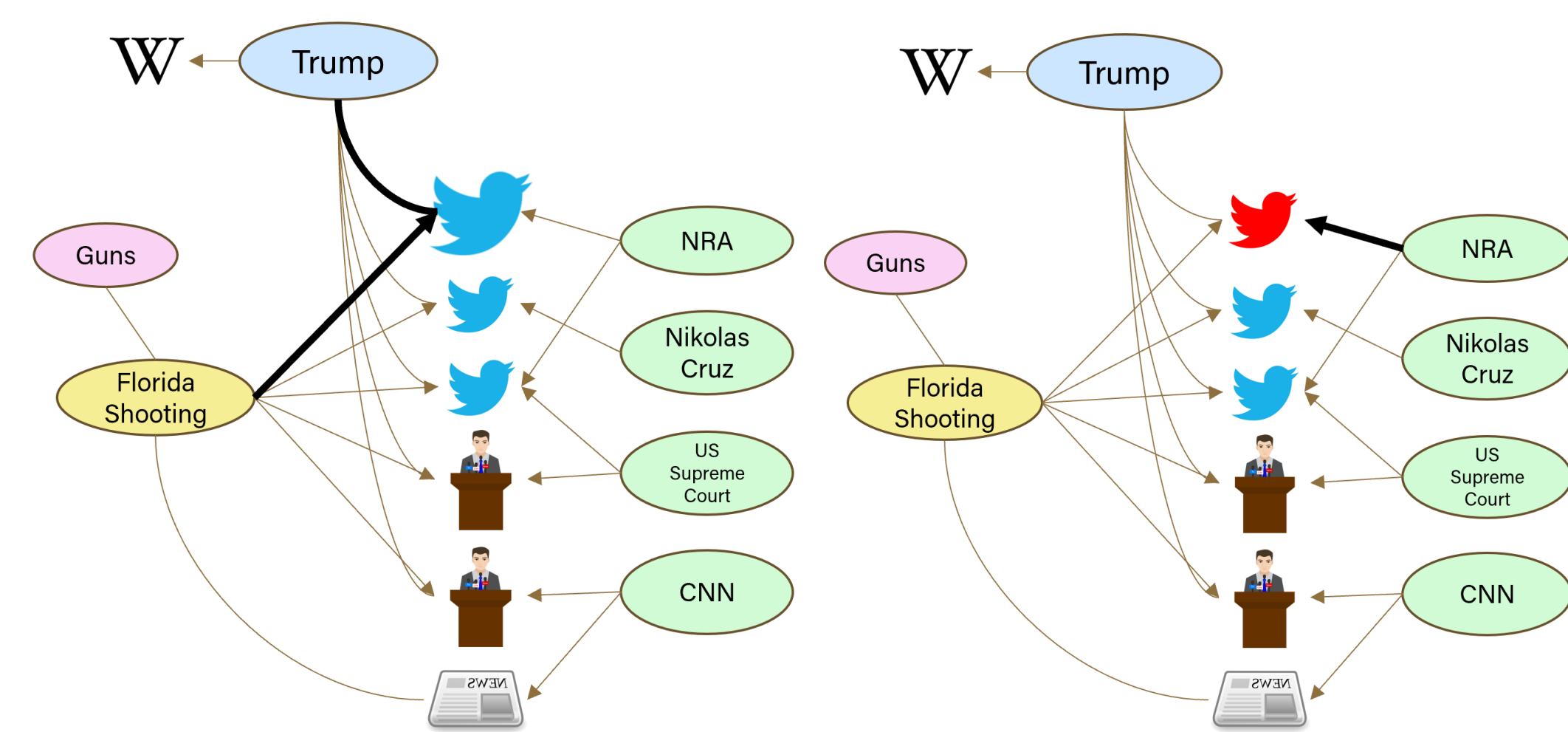
## Data Summary

- ▶ We collected US political data for 8 issues: *Guns, LGBTQ rights, Abortion, Immigration, Economic-Policy, Taxes, Middle-East & Environment*

| Data              | Count          | Data           | Count  |
|-------------------|----------------|----------------|--------|
| News Events       | 367            | Tweets         | 86,409 |
| Author Entities   | 455            | Press Releases | 62,257 |
| Ref. Entities     | 10,506         | Perspectives   | 30,446 |
| Wikipedia         | 455            | News Articles  | 8,244  |
| <b>Total Docs</b> | <b>187,811</b> |                |        |

(a) Summary Statistics of Collected Data

## Learning Tasks

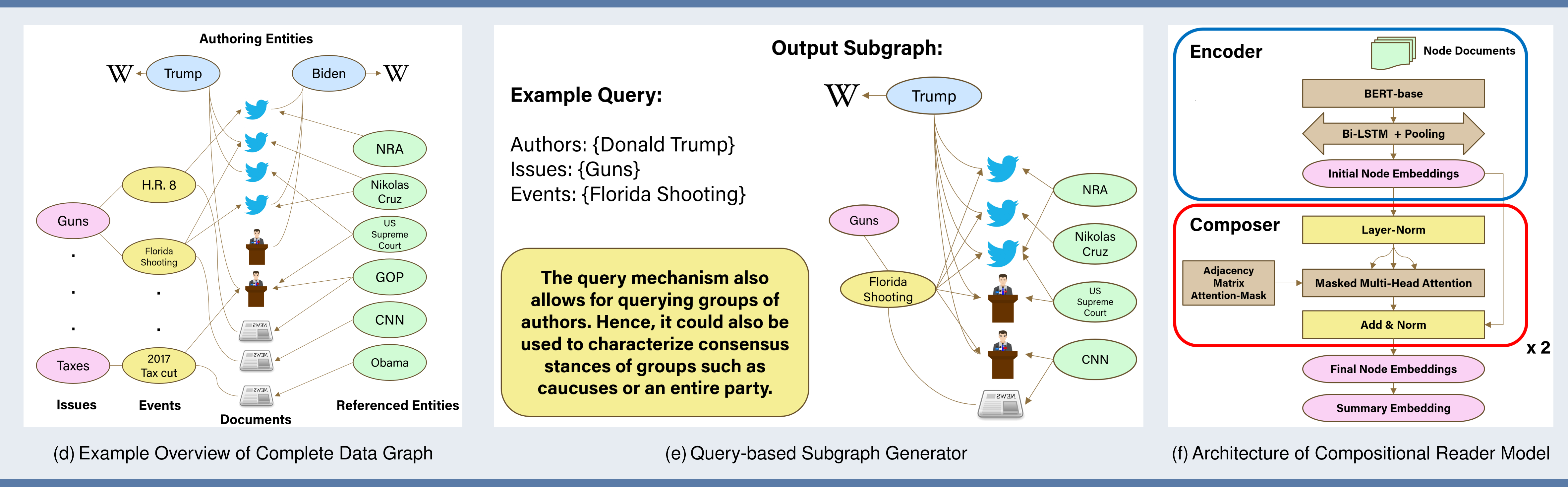


(b) Authorship Prediction: Is this tweet by Trump? (c) Referenced Entity Prediction: Is the "Donald Trump talking about Florida Shooting" masked entity in the document NRA?

## Evaluation Tasks

- ▶ We aim to evaluate how well our representations reflect the actual meaning of the text in its real-world context. We design multiple quantitative tasks and qualitative visualizations to verify our hypothesis:
  - \* Political Grade Data Alignment and Prediction
  - \* Roll-Call Vote Prediction
  - \* PCA visualizations of individual stances and group stances
  - \* Opinion Descriptor Generation
  - \* Contextualized visualization of ambiguous, opinionated text
- ▶ National Rifles Associations (NRA) and League of Conservation Voters (LCV) release issue-specific ratings of US politicians. We evaluate whether our representations are effectively able to:
  - \* Align with the grades in a zero-shot setting (Grade Paraphrase Task)
  - \* Predict grades given their public discourse (Grade Prediction Task)

## Compositional Reader Pipeline



## Learning Tasks Results

- ▶ We design a BERT adaptation baseline. Its architecture is same as Encoder's. Encoder's parameters are trained via back-propagation through Composer. BERT adaptation is directly trained on learning tasks.

| Model                              | IS Acc | IS F1 | OS Acc | OS F1 |
|------------------------------------|--------|-------|--------|-------|
| <b>Authorship Prediction</b>       |        |       |        |       |
| BERT Adap.                         | 93.01  | 92.31 | 95.56  | 95.20 |
| Comp. Reader                       | 99.49  | 99.47 | 99.42  | 99.39 |
| <b>Reference Entity Prediction</b> |        |       |        |       |
| BERT Adap.                         | 76.57  | 75.21 | 76.26  | 73.67 |
| Comp. Reader                       | 78.52  | 77.51 | 78.98  | 78.62 |

(g) Accuracy and F1 on test sets of learning tasks are reported. IS denotes In-Sample performance (test authors are included in training set). OS is Out-of-Sample performance (train and test authors are mutually exclusive).

## Quantitative Evaluation Results

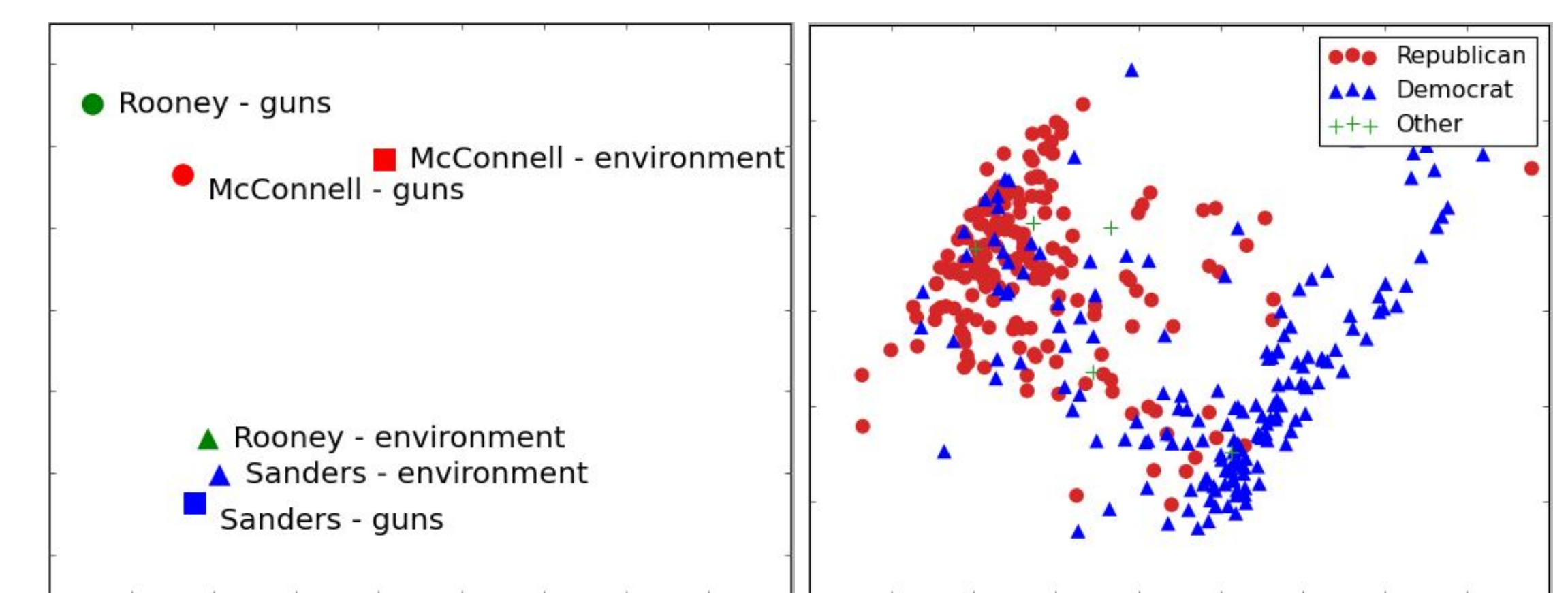
| Model        | Paraphrase All Grades | Paraphrase A/F Grades | NRA Val Acc  | NRA Test Acc | LCV Val Acc  | LCV Test Acc |
|--------------|-----------------------|-----------------------|--------------|--------------|--------------|--------------|
| BERT         | 41.55%                | 38.52%                | 55.93 ± 0.72 | 54.83 ± 1.79 | 54.28 ± 0.31 | 52.63 ± 1.21 |
| BERT Adap.   | 37.54%                | 42.62%                | 71.23 ± 3.93 | 69.95 ± 3.33 | 60.58 ± 1.56 | 59.09 ± 1.77 |
| Encoder      | 56.16%                | 48.36%                | 83.95 ± 1.24 | 81.34 ± 0.86 | 65.10 ± 0.46 | 63.42 ± 0.35 |
| Comp. Reader | 63.32%                | 63.93%                | 84.19 ± 0.98 | 81.62 ± 1.23 | 65.55 ± 1.33 | 62.24 ± 0.56 |

(h) Results of 'Grade Paraphrase' and 'Grade Prediction' tasks. Accuracy is reported. NRA and LCV denote respective Grade Prediction tasks.

| Session | Majority Class (%) | Accuracy (%) |       | Precision (%) |       | Recall (%) |       | F1 (%) |       |
|---------|--------------------|--------------|-------|---------------|-------|------------|-------|--------|-------|
|         |                    | NW-GL        | CR    | NW-GL         | CR    | NW-GL      | CR    | NW-GL  | CR    |
| 106     | 83.23              | 85.04        | 85.65 | 91.89         | 91.67 | 90.22      | 91.27 | 91.05  | 91.47 |
| 107     | 85.78              | 87.62        | 88.30 | 90.12         | 89.48 | 95.37      | 97.17 | 92.67  | 93.16 |
| 108     | 87.02              | 92.03        | 92.27 | 93.46         | 93.52 | 97.59      | 97.83 | 95.48  | 95.32 |
| 109     | 83.57              | 85.42        | 87.23 | 88.38         | 88.39 | 93.84      | 97.33 | 91.49  | 92.65 |
| Average | 84.90              | 87.53        | 88.36 | 90.96         | 90.77 | 94.26      | 95.90 | 92.67  | 93.15 |

(i) Roll Call Prediction Results. NW-GL represents the best performing model of [1] as replicated by us using their official implementation. CR represents Compositional Reader results. The improvements are statistically significant as per McNemar's test.

## Qualitative Visualizations



(j) Individual Stances

(k) Issue Guns

| Issue           | Opinion Descriptors            | Issue        | Opinion Descriptors            |
|-----------------|--------------------------------|--------------|--------------------------------|
| Mitch McConnell | Republican                     | Nancy Pelosi | Democrat                       |
| abortion        | fundamental, hard, eligible    | abortion     | future, recent, scientific     |
| environment     | achievable, more, favorable    | environment  | forest, critical, endangered   |
| guns            | foreign, meaningful, outdone   | guns         | constitutional, ironclad, fair |
| immigration     | federal, sanctuary, imminent   | immigration  | immigrant, skilled, modest     |
| Donald Trump    | Republican                     | Joe Biden    | Democrat                       |
| guns            | terrorist, public, ineffective | guns         | banning, prohibiting, ban      |
| immigration     | early, dumb, birthright        | taxes        | progressive, economic, annual  |

(l) Opinion Descriptor Labels for Politicians. They show the most representative adjectives used by the politicians in context of each issue.

## Conclusion

- ▶ We tackle the problem of understanding politics, i.e., creating unified representations of political figures, capturing their views and legislative preferences, directly from raw political discourse data originating from multiple sources.
- ▶ We propose the Compositional Reader model that composes multiple documents in one shot to form a unified political entity representation, while capturing the real-world context needed for representing the interactions between these documents.

## References

- [1] Pallavi Patil, Kriti Myer, Ronak Zala, Arpit Singh, Sheshera Mysore, Andrew McCallum, Adrian Benton, and Amanda Stent. Roll call vote prediction with knowledge augmented models. In *Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL)*, pages 574–581, Hong Kong, China, November 2019. Association for Computational Linguistics.

## Acknowledgements

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## Resources

Code: [https://github.com/pujari-rajkumar/compositional\\_learner](https://github.com/pujari-rajkumar/compositional_learner)